Incidence and Performance of Spinouts and Incumbent New Ventures: Role of Selection and Redeployability within Parent Firms

by

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Abstract

Using matched employer-employee data from 30 U.S. states, we compare spinouts with new ventures formed by incumbents (INCs). We propose a selection-based framework comprising idea selection by parents to internally implement ideas as INCs, entrepreneurial selection by founders to form spinouts, and managerial selection to close ventures. Consistent with parents choosing better ideas in the idea selection stage, we find that INCs perform relatively better than spinouts, and more so with larger parents. Regarding the entrepreneurial selection stage, we find evidence consistent with resource requirements being a greater entry barrier to spinouts and greater information asymmetry promoting spinout formation. Parents' resource redeployment opportunities are associated with lower relative survival of INCs, consistent with their being subject to greater selection pressures in the managerial selection stage.

Keyword*:* spinouts, new venture formation process, new venture performance, selection, resource redeployability

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Introduction

Spinouts—new firms founded by employees of established firms, especially in the same industry as their employer—have received particular attention from researchers in management, finance, and economics (Agarwal *et al*., 2004; Gompers, Lerner, and Scharfstein, 2005; Chatterji, 2009; Klepper, 2009). This paper aims to improve our understanding of the processes of formation, growth, and survival of spinouts by focusing on the underlying selection processes. It does so by comparing spinouts with new establishments of incumbent firms in their industries (hereafter "incumbent new ventures" or "INCs"),[1] which are direct competitors to spinouts. Such a comparison is particularly interesting and important since both types of new ventures arise from the same process of idea development and selection at incumbent firms.

Spinouts have received special attention in the strategic management literature because of their perceived greater success relative to other types of new firms. Their success is generally attributed to founders benefiting from knowledge gained at their parent firms (i.e., the firms where the founders were employed before they started the spinout, hereinafter "parents" or "incumbent firms") (Klepper, 2009; Agarwal *et al*., 2004; Chatterji, 2009).

A unique but underemphasized feature of spinouts, especially as it relates to their formation and performance, is the importance of underlying selection processes. Spinouts start as ideas generated by employees at their parents (Bernardo, Cai, and Luo, 2009), which can potentially also be selected by parents for internal implementation (Krasteva, Sharma, and Wagman, 2015). Indeed, many theories of spinout formation feature such selection (Pakes and Nitzan, 1983; Cassiman and Ueda. 2006; Nikolowa, 2014), typically modeling two levels of selection. The first stage is a parent's

[1] Examples of INCs would include Microsoft establishing a regional center for cloud computing (Microsoft Azure, 2021), Amazon setting up a tech office in Manhattan (Haag, 2020), and Intel starting a new plant in Arizona (Shead, 2021).

decision to implement (or not implement) an idea internally, either in its existing business units or by forming a new establishment. If the parent does not implement the idea, then the next layer of selection involves employees deciding to stay at their parent or leave the parent to start the spinout. This decision is typically based on the expected profits from the idea as well as employees' current earnings and incentives provided by their employer. Many studies also incorporate these selection processes into their analysis of post-entry performance of these two types of new ventures.

In contrast to these theoretical studies, most empirical studies of spinouts build on arguments about knowledge transfer from parents to spinouts or the absence of organizational inertia in spinouts (e.g., Agarwal *et al.*, 2004; Klepper and Sleeper, 2005; Carnahan, Agarwal, and Campbell, 2012). Thus, the superior performance of spinouts is attributed to knowledge developed by founders at the parent and their lack of inertia. However, selection-based arguments would suggest that INCs might do better than spinouts because parents are likely to select better ideas for internal implementation.

Thus, these arguments call for a direct comparison of spinouts and INCs on incidence as well as on performance. In practice, empirical studies that do so are rare. Most studies in this literature only examine spinouts (e.g., Agarwal *et al.*, 2004; Klepper and Sleeper, 2005; Thompson and Chen, 2011). To the extent studies have investigated aspects of the relationship between spinouts and their parents, they have focused on questions such as what types of parents spawn more spinouts (e.g., Klepper, 2009), how parents' ability to exercise competitive threats affects spinout formation and performance (Starr, Balasubramanian, and Sakakibara, 2018), and how spinout formation affects parent performance (Campbell *et al*., 2012; Agarwal *et al*., 2016). A direct comparison of how the incidence and performance of new ventures created by incumbent firms (which are identifiably distinct expansion efforts by parents) relate to the incidence and performance of spinouts is missing.

The second understudied aspect of spinouts that is also related to selection, and relevant when comparing their performance to that of INCs, is the asymmetry in the ability of incumbent firms and spinouts to redeploy their resources. Incumbent firms can potentially redeploy the resources to other businesses if the new ventures face difficulties (Lieberman, Lee, and Folta, 2017), which reduces the effective cost of starting a new venture. Such an option is less feasible for spinouts. Thus, this asymmetry in resource redeployability adds yet another layer of selection, which differentially affects the incidence and performance of spinouts and INCs.

In this study, we aim to shed light on the role of these selection processes in the incidence and performance of spinouts and INCs. We focus on three stages of selection: "idea selection" by the parent to implement an idea as an INC, "entrepreneurial selection" by the founder to form a spinout, and "managerial selection," or the decision to close a venture. We argue that, on average, INCs will perform better than spinouts because parents will choose higher-quality ideas in the idea selection stage. Furthermore, parents with greater financial resources can choose more projects in the idea selection stage, leaving fewer and lower-quality ideas for potential spinout founders for the entrepreneurial selection stage. This results in lower incidence and performance of spinouts relative to INCs for such parents. Also, parents of INCs that have greater resource redeployment opportunities can internally redeploy resources committed to INCs should the INCs fail, which reduces the risks of forming INCs in the idea selection stage. This redeployment advantage results in a higher incidence of INCs relative to spinouts. In contrast, in the managerial selection stage, greater resource redeployment opportunities imply higher opportunity costs of continuing non-performing ventures, which *reduces* the survival of INCs relative to spinouts. In the entrepreneurial selection stage, investment requirements act as a differential entry barrier to spinouts. Hence, spinouts are relatively less likely to be formed in such contexts, but those that are formed will be better-performing because they meet a higher threshold of expected performance. Lastly, in the presence of high information asymmetry between parents and employees, it may be easier for founders to leave with good ideas, resulting in relatively more and better spinouts than INCs. We examine these arguments using cross-industry matched employer-employee data covering 30 U.S. states from 1990 to 2010, and find supporting evidence.

Our study makes several important contributions to the literature on spinouts and entrepreneurship. First, we further our understanding of how selection processes may affect spinout formation and their subsequent performance by explicitly laying out and analyzing the three types of selection processes at play. In doing so, we not only link existing theoretical work with empirical evidence by focusing on underlying selection processes, but also add a complementary explanation to the dominant knowledge-based perspective adopted in empirical studies of spinouts.

Relatedly, we shed light on the links between the incidence and performance of spinouts by studying them simultaneously. There are studies on the incidence of spinouts using country-level data in such countries as Denmark (Eriksson and Kuhn, 2006; Dahl and Sorenson 2014), Brazil (Muendler, Rauch, and Tocoian, 2012), Sweden (Andersson and Klepper, 2013), and the United States using survey data on the formation of new firms by scientists and engineers (Elfenbein, Hamilton, and Zenger, 2010). However, these studies do not directly link incidence with performance. As alluded, theoretical arguments explicitly model this important relationship, but empirical studies have not examined it. We fill this gap in the literature and explore how factors that affect the incidence of spinouts also influence performance differences between spinouts and INCs.

We also contribute to our understanding of the role of resource redeployability in the entrepreneurial context. Recent theoretical arguments (e.g., Lieberman *et al*., 2017) suggest that incumbents may benefit from having more redeployment opportunities. However, empirical support for such arguments has been limited. Our study provides evidence that is consistent with these arguments; INCs of more diversified parents who are most likely to benefit from redeploying the resources have higher entry rates but significantly lower survival rates. Therefore, and a bit counterintuitively, the higher resource redeployability of diversified firms is a double-edged sword for INCs. Thus, our study also uncovers an interesting and important link between the literatures on entrepreneurial entry and resource redeployment.

Theoretical Motivation and Hypotheses Development

We conceptualize three distinct selection processes that affect the formation of INCs and spinouts and their subsequent performance. Each of these processes involves a decision either by the parent firm or the potential spinout founders, or by managers of the new ventures after entry (Figure 1). Briefly, the first is the selection of project ideas for internal implementation at the parent ("idea selection"). This is followed by "entrepreneurial selection," the decision of potential spinout founders to form spinouts. The last process, relevant after the new ventures start operating, is "managerial selection," the decision to continue or exit the new venture. We elaborate below.

Idea selection and entrepreneurial selection

We conceptualize INCs and spinouts as arising from the same process of idea selection within parents. This conceptualization follows many well-known theoretical models of spinout formation (e.g., Pakes and Nitzan, 1983; Wiggins, 1995; Cassiman and Ueda, 2006; Hellmann, 2007; Nikolowa, 2014). In a typical model, employees at a parent generate business ideas that vary in quality, and hence in expected profits. Such ideas may include product and technological improvements as well as product line and geographic market expansions. The parent then selects some of these ideas for internal implementation, typically based on the expected profits for the parent if it commercializes the idea (idea selection). Any ideas not selected by the parent are then available to employees to potentially form spinouts (i.e., for entrepreneurial selection).

In practice, parallels to these selection models can be found in studies of capital budgeting processes at firms (Harris and Raviv, 1996; Ryan and Ryan, 2002; Bernardo *et al.*, 2009). These suggest that the process of starting an INC begins with several project ideas from employees. Some of these ideas are then selected for implementation by the parent's management based on criteria that reflect project quality, such as their net present value and internal rate of return (Ryan and Ryan, 2002). In this process, firms also adopt overall capital expenditure budgets, for which the various project ideas compete (Gitman and Forrester, 1977; Ross, 1986).

To develop our hypotheses, we posit a simple decision rule that parent firms and potential spinout founders use to evaluate their implementation decisions:[2]

Expected Present Value of Profits > *Required Investment* subject to *Budget Constraint* (1)

This rule is identical to the standard net present value (NPV) criterion in corporate finance (Harris and Raviv, 1996), where firms choose projects based on their NPV. Thus, we conceptualize the selection of ideas for implementation (as INCs or as spinouts) as based on the total expected profits from the ideas, in line with previous models of spinouts (e.g., Nikolowa (2014) is based on cash flows).[3] We assume that expected profits depend on the quality of the underlying ideas and that, on average, better-quality ideas will have higher expected profits, for both parents and spinout founders.[4] Hence, for a given investment requirement and budget constraint, better-quality ideas are

[2] We present this decision model only to provide a simple exposition of our theoretical arguments. So, it does not incorporate the richness of these decisions examined in prior studies. In the Online Appendix, we offer a mathematical model that considers two dimensions of ideas—size and likelihood of success—and provides more insights into our theoretical arguments for interested readers.
[3] Equation (1) can include a scenario where parents only pursue ideas above a minimum level of total profits, while spinout founders pursue profitable but low-volume ideas that parents might not consider big enough (our model in the Online Appendix includes such a minimum). However, the rule in equation (1) would not extend to a case where the minimum is based purely on revenue, not profits.
[4] Given the theoretical focus on selection, we do not explicitly incorporate the role of parent experience and knowledge in the performance of INCs (e.g., Chen, Williams, and Agarwal, 2012) in the hypotheses development. We consider these in more detail in the Discussion section.

more likely to be selected for implementation (either as INCs, by parents, or as spinouts, by founders).

Turning to our first hypothesis on the overall relative performance of INCs and spinouts, the idea selection process described earlier implies that parents are likely to choose better-quality ideas with higher expected profits for internal implementation, leaving lower-quality ideas for spinout founders. Therefore, on average, we should expect new ventures of incumbent firms to perform better than spinouts. Hence, we have:

Hypothesis 1: On average, spinouts will perform worse than incumbent new ventures.

Factors influencing idea selection and entrepreneurial selection

We expand on the aforesaid baseline hypothesis by analyzing how parent firms and potential spinout founders may differ on the terms in equation (1) and hypothesize about how those differences may consequently shape the relative incidence and performance of INCs and spinouts. Since selection is more clearly manifested in incidence, where apt, we examine both the incidence and performance impacts to better highlight the role of selection on subsequent performance.

Parent firm financial resource availability. Focusing on budget constraints, the last term in equation (1), parents with greater financial resources are likely to have larger budgets. Hence, such parents can choose more (and larger) projects for internal implementation. Greater internal implementation not only leaves proportionately fewer ideas for potential spinout founders to explore externally but also can reduce the average quality of the ideas left for spinout founders, as more of the higher-quality ideas are picked for internal implementation. Financial resource availability at the parent also affects the propensity of potential spinout founders to leave the parent by altering their opportunity costs of leaving the firm; greater internal implementation signals to potential founders that the parent is pursuing new opportunities (Bernardo *et al*., 2009), which will decrease their propensity to leave.

A similar deterrent effect occurs when greater financial resource availability allows parents to provide better opportunities for their employees (Campbell *et al.*, 2012) or impose greater potential threats once spinouts are formed (Starr *et al*., 2018). This means fewer spinouts will be formed. Since the average quality of ideas left for spinout founder declines, the relative performance of spinouts declines as well. Hence, we predict:

Hypothesis 2a: When parents have greater financial resources, the incidence of spinouts relative to that of incumbent new ventures decreases.

Hypothesis 2b: When parents have greater financial resources, the average performance of spinouts relative to that of incumbent new ventures decreases.

Parent firm resource redeployment opportunities. Turning to required investment, the second term in equation (1), parent firms can redeploy resources from their new ventures to other parts of their operations (Lieberman *et al*., 2017), if needed. This is especially true for diversified parents, as they have greater redeployment opportunities across industries (Helfat and Eisenhardt, 2004). As Balasubramanian and Sivadasan (2008) observe, such redeployability effectively reduces the investment cost of founding an INC for parent firms by allowing them to recover part of that investment should the INC fail. This allows parents to explore ideas more easily, encouraging the entry of INCs. Hence, we predict:

Hypothesis 3: When parents have more opportunities to redeploy resources, the incidence of spinouts relative to that of incumbent new ventures decreases.

Investment requirements. Continuing with the second term in equation (1), investment requirements act as entry barriers for all new ventures, and increase the threshold of expected performance required to form a new venture. However, this effect is likely to be higher for spinouts. This is because, unlike spinout founders, parents can rely to a greater extent on internal funds, giving them an advantage with respect to the cost of capital (Schoonhoven, Eisenhardt, and Lyman, 1990). Consistent with this, research suggests that access to finance matters more for the growth of new and small firms (e.g., Aghion, Fally, and Scarpetta, 2007; Beck *et al*., 2008). These arguments suggest that we should see fewer spinouts in contexts where projects require greater investments. Moreover, since the spinouts formed in such contexts have to meet a higher threshold of expected performance, they are likely to be better performing. Thus,

Hypothesis 4a: As investment requirements increase, the incidence of spinouts relative to that of incumbent new ventures declines.

Hypothesis 4b. As investment requirements increase, the average performance of spinouts relative to that of incumbent new ventures improves.

Managerial selection at parent firms and spinouts

After the new ventures start operating, managers and entrepreneurs face the decision to exit or continue operating the new venture (managerial selection). Broadly, this decision is based on whether the expected profits from continuing exceed the opportunity costs of doing so. In this regard, one of the important factors is resource redeployability. Because parent firms can redeploy resources from their new ventures to other parts of their operations (Lieberman *et al*., 2017), their opportunity costs of continuing non-performing ventures are higher. Thus, for the same level of performance, parents are more likely to close their new ventures than spinouts. Put differently, INCs are subject to greater selection pressures after entry and thus may close earlier than spinouts. Spinouts, on the other hand, have fewer redeployment opportunities and hence are likely to survive longer. Thus,

Hypothesis 5: When parents have more opportunities to redeploy resources, the survival of spinouts relative to that of incumbent new ventures improves.

Information asymmetry and idea disclosure by employees

The underlying assumption in the preceding discussion is that employees disclose their ideas to the parent. While this is likely to be generally true due to employee fiduciary duties and legal restrictions such as trade secret laws and non-disclosure agreements, employees may sometimes be able to hide their ideas from the parent and form spinouts with those ideas. In particular, when information asymmetry between parents and their employees is high, employees can behave strategically by not revealing their ideas to the parent (Cabral and Wang, 2008; Klepper and Sleeper, 2005) and then forming spinouts with those ideas.[5] Further, such situations may also make it harder for parents to contract with their employees to reveal their ideas (Anton and Yao, 1995). Thus, when information asymmetry is high, more high-quality ideas are left unimplemented by parents for founders to form spinouts. Hence, we have:

Hypothesis 6: As information asymmetry increases, the incidence and performance of spinouts relative to that of incumbent new ventures increases.

Data and Empirical Specifications

We use two data sets from the U.S. Census Bureau: the Longitudinal Business Database (LBD) and the Longitudinal Employer Household Dynamics (LEHD). The LBD is the universe of all establishments in the United States that have at least one employee, and it contains information on employment, industry, geography, and corporate ownership. The LEHD is a composite matched employer-employee data set. We had access to data on 30 states (AR, CA, CO, FL, GA, HI, IA, ID, IL, IN, LA, MD, ME, MT, NC, NJ, NM, NV, OK, OR, RI, SC, TN, TX, UT, VA, VT, WA, WI, and WV). The LEHD provides employment history and wages of all employees who work in establishments in these states, and employment and payroll information on the corresponding

[5] Note, though, that if such strategic behavior were widespread, then spinouts would outperform INCs, in contradiction to Hypothesis 1.

employers. We use data from 1990 to 2010, excluding mining, agriculture, education, and government establishments.

Identifying incumbent new ventures and spinouts

We identify INCs as those new establishments of a firm that are in the same four-digit NAICS code as one of the firm's older establishments. Similarly, we focus on spinouts that have the same four-digit NAICS code as their parent. To identify spinouts, we follow Starr *et al*. (2018) and Benedetto *et al*. (2005) and use employee-movement data in the LEHD. Following Starr *et al.* (2018), we start with a list of new firms from the LBD. From this list, we identify spinouts as those in which at least three-quarters of employees came from an existing parent establishment and where that group of employees (the "founding cluster") did not constitute a majority of the parent establishment. This ensures that a majority of the human capital at the new firm is from the parent and that existing firms that changed their ownership are not spuriously identified as spinouts. Furthermore, following Starr *et al.* (2018), we limit spinouts to new firms for which the founding cluster had fewer than 20 employees since clusters with large numbers of employees are likely to be data errors or name changes rather than true new firms. Based on this sample selection process, we identify approximately 1.6 million INCs and spinouts, of which about 28.6% are spinouts.

Variables

Dependent variables. The dependent variables in our incidence analysis, which is performed at two levels (explained below), are the parent type (whether it spawns a spinout, INC, both, or none) and D_{SO}, a dummy variable that is 1 if a new venture is a spinout and 0 if it is an INC. We use two different measures of performance: size and survival. *Size* is defined as the logarithm of the number of employees at the new venture. *Survival* is defined as a dummy indicating whether the new venture survived to a given age. We also analyze growth implicitly by estimating specifications with size as the dependent variable and controlling for initial size.

Independent variables. We use four key independent variables that correspond to our hypotheses. First, to measure parent financial resource availability (Hypothesis 2), we use *parent size*, defined as the logarithm of the number of employees in a year. This variable has been used in prior studies as a measure of resource advantages of firms (e.g., Collins and Clark, 2003). Second, as a proxy for parent redeployment opportunities (Hypotheses 3 and 5), we use the *parent number of industries*, defined as the logarithm of the number of NAICS-4 industries a parent is present in. As observed in Lieberman *et al*. (2017), firms present in many industries are likely to have more opportunities to redeploy their resources than those present in only one industry. (We consider an alternative measure in robustness checks.) Third, we measure investment requirements (Hypothesis 4) using *industry capital intensity*, defined as the ratio of total industry assets to total industry employment obtained from Compustat. Such capital-intensive industries require large investments in physical capital, and industry capital intensity has been widely considered as an entry barrier at least since Bain (1956).

Turning to information asymmetry (Hypothesis 6), we face some limitations. To our knowledge, there are no studies that directly measure information asymmetry between employees and firms, particularly across many industries for a long period of time. Hence, in our study, we consider two different proxies that reflect some elements of information asymmetry between employees and firms even though neither is a perfect measure. As a first approach, we focus on the tacit knowledge embedded in human capital as a driver of information asymmetry. Such human-capital-embedded knowledge makes it harder for firms to evaluate the true quality of employees' ideas (Arora, 1996) and makes it easier for employees with higher-quality ideas to behave strategically and take such knowledge with them should they move from their parents. Based on these arguments, we use *industry human capital intensity* as one proxy for information asymmetry. We define it based on average industry wage (based on the LBD), commonly used as a measure of human capital (e.g., Campbell et al., 2012). In our analysis, after controlling for parent wage and other parent firm and industry characteristics described below, average industry wage is likely to reflect the importance of tacit human capital (e.g., experience, managerial skills, and knowledge) in an industry. Nonetheless, because it is a broad construct, human capital intensity could reflect aspects unrelated to information asymmetry (see Online Appendix for a discussion).

As a second approach, we borrow from studies of information asymmetry in the finance domain that focus on the asymmetry between investors and managers. Although investor-manager asymmetry is not the same as firm-employee asymmetry, they are likely to be positively correlated. In particular, if there is high information asymmetry between firms and employees, one would also expect a high degree of asymmetry between investors and managers (otherwise, one would have to assume that a firm's investors are more informed than its managers). Based on this argument, we use *average analyst earnings forecast error* in an industry, a commonly used measure of investor-manager information asymmetry in finance (e.g., Krishnaswami and Subramaniam, 1999), as a proxy. This was computed using IBES data as the industry average of the absolute forecast errors for forecasts with a horizon of 6 months or less, scaled by stock price.

Notwithstanding the similarity of results from these two distinct approaches, given the imperfectness of these measures, we interpret our results on Hypothesis 6 cautiously and leave it for future research to explore further. We also explore robustness to two other measures later.

Control variables. We include three other industry characteristics (*industry R&D intensity*, *industry advertising intensity*, and *industry growth*) and two parent characteristics (*parent age* and *parent wage*) and their interactions with the spinout dummy, where appropriate, as controls. The first set of controls ensures that our focal industry-level variables do not reflect other potential industry-level factors. *Parent age* controls for organizational inertia and knowledge differences across parents with regard to forming new ventures that may arise as firms get older. Similarly, including *parent wage* ensures that differences across firms in compensation-related incentives are not driving the results. Finally, where relevant and feasible, we include firm, state, industry, and year fixed effects to rule out the confounding impact of these factors, as discussed further below.

Empirical specifications

The hypotheses can be divided into two types—those examining relative incidence and those focusing on relative performance of spinouts vis-à-vis INCs. Our specifications follow this structure.

Relative incidence of spinouts. To examine hypotheses related to the relative incidence of spinouts (Hypotheses 2a, 3, 4a, and 6), we use two complementary specifications at two different levels.

The first specification is at the parent-year level. A possible measure of relative incidence of spinouts is the share of new ventures spawned by a parent that are spinouts. However, since almost all parents in our sample spawn only one spinout or INC in any given year, the variation in such a variable would not be very meaningful. Moreover, such a measure would also ignore the vast majority of firms that never spawn a new venture of any type. Hence, we adopt a multinomial logit specification to assess incidence. In particular, we classify parent firms into those that spawn only spinouts, those that spawn only INCs, those that spawn both types of new ventures, and those that spawn neither. Of these four categories, the last is the largest, while parents that spawn both types of new ventures form the smallest category. Since the number of observations pertaining to parents that do not spawn any type of new venture is very large, we choose a 25% random sample of such non-spawners for our analysis, while retaining all observations relating to the other types of parents and weighting our regressions accordingly. We then assess the probability of a parent firm spawning a spinout relative to spawning an INC using a multinomial logit regression with the type of parent as the dependent variable and *parent size*, *parent number of industries*, *industry capital intensity*, and *industry human capital intensity* (or *industry analyst forecast error*) as the key independent variables. We also include all controls discussed above along with year fixed effects. All independent and control variables are evaluated in the year in which the new venture is formed. We also estimate linear probability models comparing spinout-spawners to INC-spawners, including a more robust set of state-industry-year or parent and year fixed effects that are computationally infeasible in multinomial logit specifications.

Given the large number of observations, parent-year level analyses are very computationally intensive. Hence, we also adopt a second, simpler specification that is conditional on formation of a new venture, which we rely on for most of our robustness checks. In particular, we use a new venture-level sample and linear probability models with the spinout dummy D_{SO} as the dependent variable. Thus, these new venture-level regressions examine the probability that a given new venture is a spinout, and they can be interpreted as the relative incidence of spinouts conditional on formation.

Relative performance of spinouts. To test our first hypothesis about the overall difference between the performance of spinouts and INCs, we estimate age-specific regressions of the following form:

$$\pi_{ijst} = \alpha_i . D_{SO} + \theta_{jst} + \varepsilon_{ijst} \qquad (2)$$

Here, π is new venture performance (new venture size at ages 0, 3, 5, and 7, and survival at the later three ages) where subscript i denotes the new venture, j is the industry of the new venture, s denotes the state, and t is the year. D_{SO} is a dummy variable indicating a spinout, and θ_{jst} are joint state-industry-year fixed effects. Thus, the specification examines how spinouts perform relative to INCs in the same state, industry, and year. In addition to these simpler baseline specifications, we estimate a panel specification with size as the dependent variable and using all available observations for a new venture. Similarly, for survival, we also estimate an alternative specification using Cox and Weibull survival models. Further, we present robustness checks with parent and year fixed effects in the Online Appendix. (Note that many parents spawn only one of the two types of new ventures.)

To examine our hypotheses related to performance (Hypotheses 2b, 4b, 5, and 6), we use regressions similar to (2) and of the following form:

$$\pi_{ijst} = \alpha_i . D_{SO} + \boldsymbol{\beta_i} . D_{SO} \boldsymbol{Z_{jt}} + \boldsymbol{\gamma_i} . D_{SO} \boldsymbol{C_{it}} + \theta_{jst} + \varepsilon_{ijst} \tag{3}$$

As before, π is new venture performance (size at ages 0, 3, 5, and 7, and survival at the later three ages). $\boldsymbol{Z}$ denotes the variables of interest (*parent size, parent number of industries, industry capital intensity,* and *industry human capital intensity* or *industry analyst forecast error*), and $\boldsymbol{C}$ is the vector of control variables discussed above. Including interactions of the control variables with the spinout dummy also addresses the possibility that these variables have a differential effect on spinouts. As with (2), as a robustness check, we also estimate these with parent and year fixed effects.

In addition to the simpler age-specific estimations, for new venture size, we estimate a panel specification similar to (3) but containing observations across all years for a new venture. For survival, we also estimate survival models to understand how our key independent variables influence the hazard rate of exit. These specifications are computationally intensive, and so we use age-specific estimates as the baseline for most robustness checks. Other benefits of age-specific estimates are that they implicitly incorporate cohort fixed effects (since the age of all ventures in a regression is the same and year fixed effects are included) and depict any non-linear effects of age.

Throughout, unless otherwise stated, we cluster standard errors conservatively at the NAICS four-digit industry level. We cluster by new venture in the panel and survival regressions. Finally, we round the number of observations to meet Census Bureau requirements.

Results

Descriptive statistics

Panel A of Table 1 presents the means and standard deviations for key variables, while panels B and C delve into the performance differences between spinouts and INCs (correlations among variables are provided in Online Appendix Table A1a). Focusing on panel B, spinouts are smaller than INCs at every age, though the size gap shrinks as they age. More interestingly, although the mean size of both types of new ventures expectedly increases with age, their standard deviations (panel B, col. 2) move in opposite directions. Specifically, the standard deviation of spinout size *increases* with age, while that of INC size *decreases* with age. (Online Appendix Table A1b confirms this difference with formal regression tests.) This is a strong indicator that INCs close at a higher rate than spinouts, which is consistent with theoretical arguments about greater redeployability at parents of INCs. In line with this, we can see from the first row of panel C that the survival rate of INCs is *lower* than that of spinouts even though they are bigger than spinouts. Consistent with the redeployment argument, most of this difference occurs in the first few years of existence. For instance, the three-year survival rates are 64% for spinouts (vs. 59% for INCs), but the seven-year survival rates are closer (30% vs. 28%, respectively). This difference between early-life and later-life survival is starker when we compare survival from age three to age seven or from age five to age seven. In these cases, INC survival rates are the same as or *higher* than those of spinouts.

Overall performance difference between spinouts and INC

Hypothesis 1 predicts that the overall performance of spinouts would be worse than that of INCs. Table 2 presents strong supporting evidence based on the coefficient estimates from equation (2), which tests this hypothesis. (Online Appendix Tables A2a and A2b present estimates with additional controls and parent fixed effects.) From the first four columns of panel A, it is clear that compared with INCs in the same state-industry-year cohort, spinouts tend to be smaller at entry and remain smaller as they age. The estimates from the corresponding panel specification (col. 5) also points in the same direction. This difference between spinouts and INCs persists even after initial size is controlled for (last four columns), indicating that spinouts not only enter at a smaller size but also grow slower. Spinouts also tend to survive less, as seen in the first three columns of panel B, with roughly a 6–7.5% lower survival probability compared with INCs. Estimates from survival models in columns 7 and 8 (which reflect the hazard of exit) also indicate that spinouts have a greater hazard of exit than INCs. Interestingly, the difference in survival disappears when initial size is controlled for (columns 4–6).

Relative incidence of spinouts

Tables 3 and 4 present results relating to the relative incidence of spinouts (Hypotheses 2a, 3, 4a, and 6). Focusing first on the parent-year level analysis (Table 3), we can see that relative to the probability of a parent being an INC-spawner, the probability of a parent being a spinout-spawner decreases with parent size. This result can be seen across both the multinomial logit and OLS specifications and across specifications with state-industry-year and parent and year fixed effects. Thus, these results strongly support Hypothesis 2a, that when parents have greater resources, the incidence of spinouts relative to that of INC decreases. We find a similar association with the parent number of industries, which supports Hypothesis 3, that parents with more redeployment opportunities are less likely to spawn spinouts relative to INCs. We also find support, albeit weaker, for Hypotheses 4a and 6. Based on the multinomial logit specification (col. 1) and the first OLS specification (col. 3), relative to being an INC-spawner, the probability of being a spinout-spawner is lower in capital-intensive industries, which is consistent with spinouts facing a higher entry barrier in such industries (Hypothesis 4a). In contrast, but consistent with Hypothesis 6, the incidence of being a spinout-spawner is higher in industries with high information asymmetry, as seen by the positive coefficients on human capital intensity (col. 3) and analyst forecast error (col. 5), our measures of information asymmetry. However, the results on these industry-level variables are not robust to the inclusion of parent fixed effects (although they are in the same direction; cols. 4 and 6) since most parents tend to be in one industry and variations in these variables tend to be small within industries.

The inferences regarding the relative incidence of spinouts and INCs remain unchanged when we analyze using the new-venture-level sample (Table 4). In this table, each observation is a new establishment. The dependent variable is a dummy that is 1 if the new establishment is a spinout and 0 if the new establishment belongs to a parent. Conditional on formation, the probability of a new venture being a spinout is decreasing in parent size, parent number of industries, and industry capital intensity (weakly), but increasing (weakly) in industry human capital intensity and analyst forecast error. These results are all consistent with our hypotheses.

Relative performance of spinouts

Tables 5 through 8 present results from our analyses of the relative performance of spinouts. Table 5 examines the size of the two types of entrants within the same state-industry-year at different ages. Panel A uses *industry human capital intensity*, and panel B uses *average analyst earnings forecast error in an industry* as the measure of information asymmetry. The last three columns include controls for initial size-state-industry-year fixed effects, thus providing an analysis of the growth patterns of the new ventures. Table 6 reexamines relative size using a panel specification that includes all observations available for a new venture. The next two tables examine relative survival, with age-specific OLS estimates in Table 7 and survival models in Table 8.

Focusing first on Hypothesis 2b about parent resource availability aiding INCs, the estimated coefficients in Tables 5 and 6 are in the predicted direction. Consistent with the argument that firms with greater resources spawn lower-performing spinouts (relative to INCs), the coefficients on the spinout dummy–parent size interaction terms are uniformly negative in all specifications in both the age-specific (Table 5, row 2) and panel estimates (Table 6, row 2). The direct term on parent size is positive, indicating that larger parents form larger (and faster-growing) INCs. This term is generally larger in magnitude than the coefficient on the spinout dummy–parent size interaction term. Thus, this indicates that though larger parents spawn larger spinouts (consistent with studies such as Agarwal, Sarkar, and Echambadi, 2002), they establish even larger INCs, which manifests as a lower relative size of spinouts. The results with survival as a performance measure are similar, though somewhat weaker. The results from the survival models (Table 8, row 1) are consistent with spinouts from larger parents facing a larger hazard of exit (relative to INCs), but the coefficients are small and insignificant in the age-specific estimates (Table 7, row 2). On balance, the evidence across these four sets of estimates supports Hypothesis 2b.

Our results strongly support Hypothesis 5 that predicts a higher relative survival rate for spinouts spawned by parents with greater redeployment opportunities. This can be seen in Tables 7 and 8. In the age-specific estimates (Table 7, row 3), the coefficients on the spinout dummy–parent number of industries interaction terms are positive throughout. Consistent with our arguments, the coefficient on the parent number of industries (direct term, row 7) is negative and significant. Thus, these results suggest that as parents' opportunities for redeploying resources outside the industry increase, the selection pressure on INCs increases, and correspondingly, their survival decreases. This can also be seen in the margins estimates from the survival models (Table 8, row 2) where the hazard of exit for spinouts (relative to INCs) decreases as the parent number of industries increases.[6]

[6] Specifically, we present the difference between the marginal effect of a variable on spinouts vs. INCs. Formally, for a variable of interest, *x*, this is $(\frac{dy}{dx})_{SO} - (\frac{dy}{dx})_{INC}$. The underlying coefficients from these models are presented in Online Appendix Table A8a.

We also find some support for Hypothesis 4b, which predicts that the negative performance difference between spinouts and INCs will shrink as investment requirements for forming a new venture increase. The positive coefficients on the industry capital intensity-spinout dummy interaction term indicate that the relative size of spinouts increases with industry capital intensity in both the age-specific (Table 5, row 4) and panel estimates (Table 6, row 4), both with and without initial size controls. This implies that the size and growth differences between spinouts and INCs are smaller in capital-intensive industries than in other industries. Turning to survival, the corresponding coefficients in the age-specific OLS estimates (Table 7, row 4) are insignificant. The coefficients on capital intensity in survival model estimates are generally negative (Table 8, row 3), consistent with the hypothesis, although the models with the least robust set of fixed effects are positive.

Finally, with regard to information asymmetry, Hypothesis 6 predicts a higher relative performance for spinouts in contexts with high information asymmetry. Consistent with this, both measures of industry information asymmetry are generally associated with a higher relative performance of spinouts. Focusing on relative size first, the interaction terms (Table 5, row 5, in each panel) are mostly positive, and mostly statistically significant when initial size is controlled for. Similarly, the coefficients on the interaction term are positive and statistically significant in the panel specifications (Table 6, rows 5 and 6). With regard to survival, the coefficients from the age-specific OLS estimates (Table 7, row 5) and survival models (Table 8, rows 4 and 5) all indicate that spinouts are more likely to survive (or less likely to exit) in industries with high information asymmetry. Together, these results appear to support Hypothesis 6.

Robustness checks

Alternative specifications and samples. We reestimate our results using parent and year fixed effects, and find similar results (Online Appendix Tables A2b, A5a, A6a, A7a). As another alternative to survival models and age-specific estimations, we estimate panel regressions with an exit dummy (which is 1 if the new venture exited, and 0 otherwise). The results are very similar to the baseline specifications (results not presented). As another check, we reestimate the baseline incidence and performance regressions excluding parents that spawned only one new venture. Excluding such singletons does not qualitatively change the results (results not presented). We reestimate our results by restricting our sample to those new ventures that had no more than 20 employees in the first year (the size cutoff used to define spinouts). Our results are qualitatively similar and in the expected direction; the size differentials are still negative but smaller than our baseline, as we would expect if there were many INCs that started with more than 20 employees (results not reported due to disclosure risks to the U.S. Census Bureau). Finally, we reestimate our baseline incidence specification with initial size as a control (Table A4b) and our performance specifications with initial size entered linearly along with its interaction with the spinout dummy (Tables A5c and A7c). The results remain robust.

Alternative measures. We reestimate our incidence results using an alternative dependent variable, the share of spinouts of all new ventures spawned by the parent. The results presented in Online Appendix Table A3c are similar to our baseline results. We then test the robustness of results related to survival using a different measure of redeployability, *parent's diversification relatedness,* which accounts for potential differences in redeployability depending on the relatedness of industries. Specifically, we calculate a relatedness measure as the mean of the logarithmic "distance" between all the NAICS four-industry pairs a firm is present in. The "distance" between any two industries is computed as the ratio of the number of firms present in both industries to the total number of firms in either industry. Thus, closely related industry pairs have a higher value of this distance measure, and potentially allow for easier resource redeployability. The results are presented in Table A7d of the Online Appendix, and are similar to the baseline results in Tables 5 and 7. Redeployability continues to be negatively associated with survival, consistent with Hypothesis 5b.

Along the same lines as above, we reestimate our results using two different measures of information asymmetry. As one alternative, we use the *share of technical employees in industry employment* as another proxy of information asymmetry since such employees are more likely to have tacit knowledge that could be used to form a spinout. As another alternative, we identify a set of industries where trade secret lawsuits are common (Lerner, 2006) and use a dummy for *industries with high trade secret lawsuits* as a proxy for information asymmetry between firms and employees. The incidence and performance results are presented in the Online Appendix (Tables A3b, A4a, A5b, and A7b) and are qualitatively similar.

Discussion and Conclusion

Significance of findings

This study uses a matched employer-employee data set of new ventures covering 30 U.S. states to compare the incidence and performance of spinouts and INCs. We discuss three different kinds of selection inherent in the process of spinout formation and offer a parsimonious framework that considers the initial idea selection by the parent, the entrepreneurial selection by the founder to form a spinout, and the eventual managerial selection to close an underperforming venture. Our results are consistent with these different types of selection having large, interesting effects on the relative incidence and performance of spinouts.

In line with parent firms choosing better-quality ideas (idea selection), a direct comparison of spinouts and INCs reveals that spinouts tend to underperform relative to INCs. This finding runs somewhat counter to the generally observed superior performance of spinouts relative to other types of new ventures. Based on Table 2, panel A, on average, INCs are more than twice the size of spinouts when they start (log employment of 1.76 vs. 0.82), and remain larger at least until seven years of age, when they are about 50% larger than spinouts (log employment of 2.47 vs. 2.07). This finding, along with our other findings, not only provides empirical evidence to theoretical studies of spinout formation (e.g., Nikolowa, 2014) but also adds to the body of work on the performance of spinouts (e.g., Agarwal *et al*., 2002; Campbell *et al*., 2012).

Consistent with our arguments about idea selection that parents with greater resources can select more and better-quality ideas for internal implementation, we find that both relative incidence and performance of spinouts decline with parent size. To our knowledge, our study is the first to highlight these patterns. As another novelty, our results highlight the role of resource redeployability in the context of entrepreneurship. From the regression results in Table 7, a one-standard-deviation increase in the parent number of industries (1.14) is associated with an increase in the relative survival rate of spinouts in the first seven years by about 4.6 percentage points (0.041 times 1.14). Furthermore, the coefficients on the parent number of industries (direct term, row 7) are negative and significant. These results are consistent with our managerial selection arguments that INCs face greater selection pressures due to the greater redeployment opportunities of parents. Furthermore, consistent with arguments that resource redeployability may make it easier for parents to form INCs, the relative incidence of spinouts declines with resource redeployability.

Our findings also suggest a role for financial resource requirements and information asymmetry in the decision of potential spinout founders to enter the market (entrepreneurial selection). While the latter is beneficial to spinouts, the former acts as an entry barrier for them. A one-standard-deviation increase in industry capital intensity is associated with a decrease in the probability of a new venture being a spinout by about 3.5 percentage points (1.75 times –0.020 from Table 4, col. 1). With regard to information asymmetry, an increase of one standard deviation in industry human capital intensity is associated with an increase in relative incidence of spinouts by about 6.1 percentage points (0.69 times 0.089). The corresponding figure for industry analyst forecast error is about 0.6 percentage points (0.16 times 0.04).

Non-observability of ideas

We now comment on a potential limitation of our analysis. Even though ideas play an important role in our theory and many theoretical papers rely on the notion of ideas, we do not directly observe ideas in our data. Rather, our inferences are made indirectly based on the outcomes of ideas, *viz*, incidence and performance of new ventures. In this regard, readers should note that we are not estimating the causal impact of being a spinout or an INC. That is, we do not want to estimate how performance would change if an idea were implemented as an INC rather than as a spinout. Hence, the implications of unobservability of ideas here are a bit different from the standard omitted variable bias problem (where unobservable quality is part of the error term and induces a correlation with some variable of interest resulting in biased regression estimates). Here, we are *hypothesizing* about the unobserved quality of ideas and how such quality may correlate with the different variables of interest due to selection processes at play. Rather, the potential problem is that our results are driven by processes other than selection (we comment on this in the next subsection). Indeed, if there were complete data on the quality of all ideas (including those that were rejected for implementation), one could directly examine if our arguments related to idea quality and selection are correct. For instance, one could examine if ideas that result in INCs have higher quality than those that result in spinouts (Hypothesis 1). Since we do not have access to data on ideas (which are probably unlikely to be available or even infeasible to observe), our analysis makes indirect inferences based on external manifestations of those ideas, *viz.* the new ventures. While our approach of looking at incidence and performance simultaneously helps address some of the limitations associated with unobservable ideas, our inferences nonetheless rely on a positive correlation between the quality (or more specifically, the expected profits) of the unobserved ideas and the performance of the new ventures formed based on those ideas. In addition, our inferences also rely on the assumption that any ideas that were not translated into new ventures were, on average, of lower quality than those that were implemented as new ventures. Though these assumptions are reasonable, and fully consistent with prior theoretical studies, we cannot directly test their validity.

Nonetheless, three pieces of evidence provide some comfort. First, we estimate regressions (for spinouts only) of new venture size on the founding cluster size (i.e., the number of individuals in the cluster that moves from the parent to the spinout) and find that the two are very highly correlated. Hence, to the extent a larger founding cluster size is indicative of better ideas, that also appears to be reflected in venture size. (We cannot run a similar regression for INCs since we cannot meaningfully define cluster size. Relatedly, our baseline inferences remain qualitatively similar when we exclude spinouts that had a cluster size of one.) Second, we examine if patent ownership (as a rough proxy for idea quality) varies between spinouts and incumbents. In order to do so, we use the concordance developed by researchers at the Census Bureau. We find that spinouts are much less likely to be classified as patent owners than INCs in the first three years of their existence, after controlling for parent firm characteristics such as size and age (Online Appendix, Table A9). Though this analysis is somewhat imprecise because the concordance is at the firm level, nonetheless, the evidence is broadly consistent with the argument that spinouts tend to be of lower quality than INCs. (We attempted additional analyses based on patent data but were hampered by the low incidence of patent-owning spinouts in the data.). Finally, we examine how the enforceability of noncompete agreements (which make it costlier to form spinouts that directly compete with their parents) was associated with the relative incidence and performance of spinouts. Consistent with selection-based arguments, we find that in states with higher enforceability, the relative incidence of spinouts is lower while their relative performance tends to be higher (Tables A10 and A11 in the Online Appendix).

Alternate mechanisms

It is important to note that though our framework focuses on selection, it does not imply that there are no other mechanisms influencing the formation and performance of spinouts and INCs. We elaborate on two of the most widely studied and relevant mechanisms, and discuss the impact of those mechanisms within the context of our framework and findings.

Knowledge transfer from parents. The first alternate mechanism relates to the role of the parent in the spinout founder's knowledge acquisition. Influential studies of spinouts such as Agarwal *et al*. (2002, 2004) and Chatterji (2009) observe that spinout founders gain knowledge at their parents, which may explain the observed superior performance of spinouts relative to other types of new ventures. Consistent with this, Agarwal *et al*. (2002) and Hvide (2009) find that larger firms spawn better-performing spinouts. Our findings on spinout size are indeed consistent with these findings; the total effect of parent size on the size and growth of spinouts (Tables 5 and 6) is positive, indicating that larger firms spawn larger spinouts (even though they are still smaller relative to the INCs). Such knowledge acquisition also explains why larger firms may form more spinouts (Agarwal *et al*. 2004).

More broadly, our framework encompasses some forms of knowledge transfer arguments. Specifically, the concept of parent resource availability can be interpreted to include parent knowledge that allows *both* spinout founders and parents to start larger ventures, but benefits INCs more than spinouts. For instance, Chen *et al.* (2012) find that parents may have valuable experience and integrative knowledge that benefits their ventures. Both INCs and spinout founders can leverage such knowledge and experience, but given their tighter organizational relationship with the parent, it is not unreasonable to expect that INCs may benefit more than spinout founders. Hence, such knowledge and experience availability at parents would increase the absolute performance of spinouts, but decrease their relative performance compared with INCs.

Note, however, that a knowledge transfer argument that does not consider some form of selection or redeployability would imply a higher survival rate for both types of new ventures if they are from larger parents, rather than the lower rate that we find for INCs. Similarly, an alternative explanation is that INCs have superior performance over spinouts because only well-performing incumbents start INCs. However, we observe a lower survival rate for INCs, which is inconsistent with only well-performing incumbents starting INCs. Hence, some form of selection or redeployability will again be needed to explain the lower survival rate.

Incentives and competitive threats from parents. The second mechanism relates to the role of incentives and competitive threats parents can use to deter spinout founders. For instance, Campbell *et al*. (2012) find that highly paid employees are less likely to leave a firm, but when they do, they are more likely to start a spinout. Similar arguments can be found in Elfenbein *et al*. (2010), who find that employees of a larger firm may be deterred from entrepreneurship because of the higher opportunity cost of leaving the parent. Parents can also deter spinout formation by direct competitive threats or actions such as competing intensely with the spinouts in the output or input markets (Walter, Heinrichs, and Walter, 2014; Starr *et al*., 2018; Sakakibara and Balasubramanian, 2020). For the sake of parsimony, we do not explicitly incorporate this deterrent effect in our theory. Nonetheless, in our empirical analyses, we include parent wage and its interaction with new venture type as a control for the incentive-related effects of being at a larger parent. Similarly, to rule out the potential direct competitive effect of a larger parent, we confirm the robustness of our baseline results by including the parent’s industry (or state-industry) market share and its interactions as controls.

Together, these arguments and findings highlight the role selection processes play beyond those of other mechanisms in determining the incidence and performance of spinouts and INCs.

Implications for research

Our study has several implications for the study of strategic management and entrepreneurship. First, our study adds selection processes as a complementary explanation to the knowledge-based perspectives that have been widely used in studies of spinouts. Our results suggest that incorporating selection-based arguments may provide a richer understanding of the formation and subsequent performance of spinouts. Among others, selection-based arguments may provide studies of spinouts with a better understanding of the linkage between incidence and performance. Studies may also benefit from developing more fine-grained measures of factors that affect selection. Another avenue for future research could be to incorporate individual-level measures into studies of selection. Second, our study suggests that industry condition may play a role in determining the incidence and performance of spinouts. In particular, this study suggests a role for financial resource requirements and information asymmetry. Future studies on spinouts can further explore these and other industry contexts. Lastly, our study suggests that resource redeployability plays an interesting role in understanding spinout performance, especially when compared with other types of new ventures. Further investigation on its role in an entrepreneurial context is likely to be meaningful.

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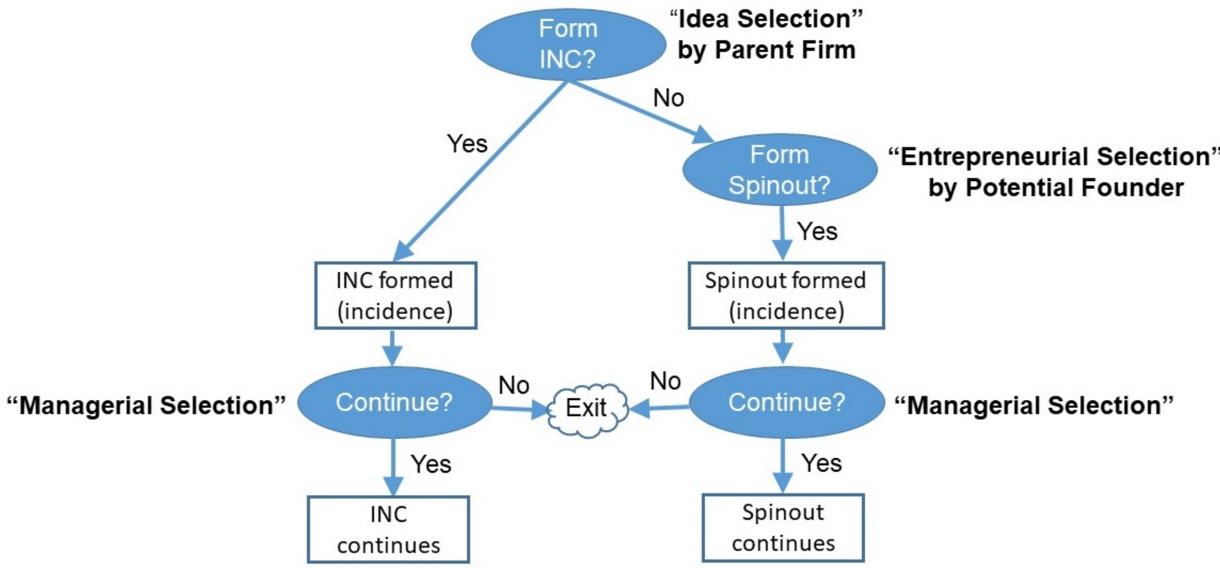

Figure 1: Selection processes in formation and continuation of spinouts and incumbent new ventures

Table 1: Descriptive statistics

Panel A: Means and standard deviations

Variable	Mean	Std. dev.
Dependent variables		
Spinout dummy variable (D_{SO})	0.29	0.45
New venture size (age 0)	1.49	1.35
New venture size (age 3)	1.84	1.35
New venture size (age 5)	1.96	1.36
New venture size (age 7)	2.07	1.36
Explanatory variables		
Parent size	7.26	3.45
Parent number of industries	1.30	1.14
Industry capital intensity	5.38	1.75
Industry human capital intensity	3.47	0.69
Industry analyst forecast error	0.02	0.16
Control variables		
Industry R&D intensity	0.00	0.02
Industry advertising intensity	0.01	0.02
Industry growth	0.04	0.27
Parent wage	3.27	0.81
Parent age	2.83	0.77

N = 1,628,000 (rounded); Correlations presented in Online Appendix Table A1a.

Panel B: Size differences

	Mean	Std. dev
Spinouts		
New venture size (age 0)	0.82	0.88
New venture size (age 3)	1.09	0.98
New venture size (age 5)	1.19	1.01
New venture size (age 7)	2.07	1.36
Incumbent new ventures		
New venture size (age 0)	1.76	1.41
New venture size (age 3)	1.84	1.36
New venture size (age 5)	2.31	1.35
New venture size (age 7)	2.47	1.33

Panel C: Survival differences

	Spinouts			Incumbent new ventures		
	To at least age 3	To at least age 5	To at least age 7	To at least age 3	To at least age 5	To at least age 7
From age 0	64%	45%	30%	59%	40%	28%
From age 3		70%	47%		68%	47%
From age 5			67%			70%

Table 2: Relative overall performance of spinouts and incumbent new ventures

Panel A: Size

	(1) **Age 0**	**(2)** **Age 3**	**(3)** **Age 5**	**(4)** **Age 7**	**(5)** **Panel**	**(6)** **Age 3**	**(7)** **Age 5**	**(8)** **Age 7**	**(9)** **Panel**
D_{SO}	**–1.134**	**–1.160**	**–1.168**	**–1.176**	**–1.132**	**–0.350**	**–0.391**	**–0.431**	**–0.230**
	(0.074)	(0.076)	(0.075)	(0.072)	(0.003)	(0.074)	(0.074)	(0.077)	(0.003)
N	1,628,000	976,000	663,000	458,000	9,340,000	976,000	663,000	458,000	9,340,000
R^2	0.321	0.375	0.401	0.425	0.311	0.828	0.825	0.832	0.777
Fixed effects	St.-ind.-year	St.-ind.-year	St.-ind.-year	St.-ind.-year	St.-ind.-year	St.-ind.-year-init.size	St.-ind.-year-init.size	St.-ind.-year-init.size	St.-ind.-year-init.size

Robust standard errors clustered by NAICS four-digit industry for age-specific models and by new venture for other models, shown in parentheses. Coefficients with *p*-values below 10% highlighted in bold.

Panel B: Survival/Exit

	(1) **Age 3** **OLS**	**(2)** **Age 5** **OLS**	**(3)** **Age 7** **OLS**	**(4)** **Age 3** **OLS**	**(5)** **Age 5** **OLS**	**(6)** **Age 7** **OLS**	**(7)** **Cox**	**(8)** **Weibull**
D_{SO}	**-0.076**	**-0.072**	**-0.057**	0.004	0.009	0.012	**0.228**	**0.232**
	(0.024)	(0.027)	(0.023)	(0.024)	(0.025)	(0.022)	(0.020)	(0.021)
N	1,628,000	1,628,000	1,628,000	1,628,000	1,628,000	1,628,000	1,628,000	1,628,000
R^2	0.342	0.372	0.381	0.557	0.593	0.611		
Fixed effects	St.-ind.-year	St.-ind.-year	St.-ind.-year	St.-ind.-year-init.size	St.-ind.-year-init.size	St.-ind.-year-init.size	State, Naics4, year	State, Naics4, year

OLS models reflect probability of survival. Cox and Weibull models reflect hazard of exit. Robust standard errors clustered by NAICS four-digit industry for age-specific models and by new venture for other models, shown in parentheses. Coefficients with *p*-values below 10% highlighted in bold.

Table 3: Relative incidence of spinouts (parent-year level sample)

	(1) MLOGIT SO vs. INC spawners	**(2) MLOGIT SO vs. INC spawners**	**(3) OLS SO vs. INC spawners**	**(4) OLS SO vs. INC spawners**	**(5) OLS SO vs. INC spawners**	**(6) OLS SO vs. INC spawners**	**(7) OLS SO vs. INC spawners**
Parent size	**–0.407**	**–0.434**	**–0.060**	**–0.011**	**–0.064**	**–0.011**	**–0.048**
	(0.030)	(0.038)	(0.005)	(0.003)	(0.007)	(0.003)	(0.006)
Parent number of industries	**–1.414**	**–1.416**	**–0.231**	**–0.041**	**–0.231**	**–0.041**	**–0.245**
	(0.103)	(0.107)	(0.023)	(0.009)	(0.023)	(0.009)	(0.024)
Industry capital intensity	**–0.295**	**–0.211**	**–0.040**	–0.002	**–0.030**	–0.002	
	(0.117)	(0.118)	(0.019)	(0.006)	(0.018)	(0.006)	
Ind. human capital intensity	**0.804**		**0.069**	0.002			
	(0.155)		(0.016)	(0.007)			
Ind. analyst forecast error		**0.152**			**0.015**	0.002	
		(0.085)			(0.004)	(0.008)	
Controls							
Industry R&D intensity	0.100	2.043	0.168	0.001	0.391	0.006	
	(2.949)	(3.214)	(0.383)	(0.159)	(0.431)	(0.159)	
Industry adv. intensity	1.671	–2.339	0.245	–0.013	–0.186	–0.017	
	(2.526)	(2.720)	(0.254)	(0.303)	(0.278)	(0.304)	
Industry growth	–0.034	–0.033	0.001	–0.003	0.002	–0.003	
	(0.079)	(0.087)	(0.007)	(0.005)	(0.010)	(0.005)	
Parent wage	**–0.538**	**–0.198**	**–0.020**	**–0.016**	–0.001	**–0.016**	**–0.023**
	(0.049)	(0.089)	(0.004)	(0.004)	(0.007)	(0.004)	(0.004)
Parent age	**–0.552**	**–0.570**	**–0.049**	**0.007**	**–0.049**	0.007	**–0.031**
	(0.036)	(0.039)	(0.007)	(0.007)	(0.007)	(0.007)	(0.005)
N	17.84 m	17.84 m	544,000	544,000	544,000	544,000	544,000
R^2	0.168	0.165	0.541	0.905	0.535	0.905	0.697
Fixed effects	Year	Year	State-year	Parent, year	State-year	Parent, year	St.-ind.-year

The first two columns present estimates from multinomial logit regression with INC spawners set as the base category. Only estimates for spinout spawners presented. Estimates for the other two categories—non-spawners and both-spawners—are provided in Online Appendix Table A3a. Pseudo-R^2 presented in first two columns. Robust standard errors clustered by NAICS four-digit industry in parentheses. Coefficients with *p*-values below 10% highlighted in bold.

Table 4: Relative incidence of spinouts (new venture level sample)

	(1) OLS	(2) OLS	(3) Logit	(4) Logit	(5) OLS	(6) OLS	(7) OLS	(8) OLS
Parent size	**–0.072**	**–0.074**	**–0.547**	**–0.561**	**–0.065**	**–0.063**	**–0.010**	**–0.011**
	(0.004)	(0.004)	(0.029)	(0.032)	(0.004)	(0.004)	(0.002)	(0.002)
Parent number of industries	**–0.021**	**–0.019**	**–0.982**	**–1.005**	–0.014	–0.017	**–0.009**	**–0.014**
	(0.011)	(0.01093)	(0.089)	(0.086)	(0.010)	(0.011)	(0.003)	(0.004)
Industry capital intensity	**–0.020**	–0.007	**–0.307**	**–0.200**			0.001	0.001
	(0.007)	(0.006)	(0.104)	(0.101)			(0.003)	(0.003)
Industry human capital intensity	**0.089**		**0.755**				0.006	
	(0.018)		(0.155)				(0.007)	
Ind. analyst forecast error		**0.040**		**0.308**				0.004
		(0.015)		(0.170)				(0.015)
Controls								
Industry R&D intensity	–0.119	0.351	1.645	5.308			0.117	0.160
	(0.595)	(0.639)	(5.145)	(5.250)			(0.176)	(0.178)
Industry advertising intensity	0.083	–0.662	–0.288	–6.048			0.114	0.054
	(0.435)	(0.499)	(3.379)	(3.891)			(0.145)	(0.149)
Industry growth	0.003	0.003	–0.039	0.009			–0.005	–0.004
	(0.011)	(0.014)	(0.074)	(0.089)			(0.004)	(0.004)
Parent wage	**–0.053**	**–0.027**	**–0.354**	**–0.104**	**–0.062**	**–0.061**	**–0.010**	**–0.013**
	(0.008)	(0.010)	(0.058)	(0.068)	(0.008)	(0.008)	(0.003)	(0.004)
Parent age	**–0.094**	**–0.098**	**–0.499**	**–0.510**	**–0.074**	**–0.069**	**0.039**	**0.016**
	(0.012)	(0.012)	(0.050)	(0.049)	(0.010)	(0.009)	(0.006)	(0.007)
N	1,628,000	1,628,000	1,628,000	1,628,000	1,628,000	1,628,000	1,628,000	1,628,000
R^2	0.590	0.582	0.609	0.602	0.657	0.695	0.889	0.889
Fixed effects	State-year	State-year	State, year	State, year	Industry-year	St.-ind.-year	Parent, year	Parent, year

Pseudo-R^2 presented in column 7. Robust standard errors clustered by NAICS four-digit industry in parentheses. Coefficients with *p*-values below 10% highlighted in bold.

Table 5: Relative size of spinouts and parent and industry characteristics (age-specific estimations)

Panel A	**Age 0**	**Age 3**	**Age 5**	**Age 7**	**Age 3**	**Age 5**	**Age 7**
D_{SO}	**–2.051**	**–1.309**	**–1.018**	**–0.703**	**–0.663**	**–0.572**	–0.398
	(0.338)	(0.342)	(0.368)	(0.406)	(0.177)	(0.206)	(0.272)
D_{SO} x Parent size	–0.023	**–0.082**	**–0.105**	**–0.116**	**–0.052**	**–0.056**	**–0.060**
	(0.027)	(0.026)	(0.027)	(0.028)	(0.014)	(0.015)	(0.016)
D_{SO} x Parent number of industries	0.013	0.067	**0.102**	**0.117**	**0.074**	**0.082**	**0.079**
	(0.055)	(0.042)	(0.046)	(0.051)	(0.028)	(0.031)	(0.035)
D_{SO} x Industry capital intensity	**0.131**	**0.119**	**0.121**	**0.128**	**0.046**	**0.067**	**0.084**
	(0.031)	(0.036)	(0.040)	(0.044)	(0.017)	(0.018)	(0.025)
D_{SO} x Industry human capital intensity	0.063	0.073	0.022	–0.011	**0.145**	**0.077**	0.055
	(0.068)	(0.071)	(0.070)	(0.070)	(0.047)	(0.045)	(0.049)
Parent size	**0.082**	**0.162**	**0.185**	**0.198**	**0.082**	**0.089**	**0.098**
	(0.027)	(0.025)	(0.027)	(0.028)	(0.015)	(0.015)	(0.015)
Parent number of industries	**–0.162**	**–0.248**	**–0.268**	**–0.279**	**–0.136**	**–0.141**	**–0.147**
	(0.057)	(0.042)	(0.046)	(0.049)	(0.030)	(0.029)	(0.031)
N	1,628,000	976,000	663,000	458,000	976,000	663,000	458,000
R^2	0.329	0.394	0.424	0.451	0.831	0.828	0.835

Panel B	**Age 0**	**Age 3**	**Age 5**	**Age 7**	**Age 3**	**Age 5**	**Age 7**
D_{SO}	**–1.941**	**–1.181**	**–0.966**	**–0.686**	**–0.419**	**–0.292**	**–0.425**
	(0.278)	(0.281)	(0.312)	(0.339)	(0.154)	(0.077)	(0.049)
D_{SO} x Parent size	–0.024	**–0.083**	**–0.105**	**–0.116**	**–0.053**	0.002	0.000
	(0.027)	(0.026)	(0.027)	(0.028)	(0.015)	(0.008)	(0.007)
D_{SO} x Parent number of industries	0.012	0.066	**0.101**	**0.117**	**0.072**	**0.032**	**0.029**
	(0.054)	(0.042)	(0.046)	(0.051)	(0.028)	(0.017)	(0.013)
D_{SO} x Industry capital intensity	**0.144**	**0.134**	**0.124**	**0.122**	**0.077**	0.008	**0.019**
	(0.033)	(0.037)	(0.041)	(0.045)	(0.022)	(0.008)	(0.006)
D_{SO} x Ind. analyst forecast error	–0.015	0.033	0.020	0.052	**0.090**	**0.024**	**0.023**
	(0.099)	(0.123)	(0.113)	(0.096)	(0.030)	(0.008)	(0.005)
Parent size	**0.082**	**0.162**	**0.186**	**0.199**	**0.081**	**–0.017**	**–0.012**
	(0.027)	(0.025)	(0.027)	(0.028)	(0.015)	(0.008)	(0.007)
Parent number of industries	**–0.161**	**–0.247**	**–0.268**	**–0.280**	**–0.133**	**–0.015**	**–0.024**
	(0.057)	(0.042)	(0.047)	(0.050)	(0.029)	(0.016)	(0.013)
R^2	0.329	0.394	0.424	0.451	0.831	0.828	0.835
N	1,628,000	976,000	663,000	458,000	976,000	663,000	458,000

Coefficients on controls not presented. Robust std. errors clustered by NAICS 4 industry in parentheses. State-industry-year fixed effects included in the first four columns; initial size-state-industry-year fixed effects included in the last three columns. *p*-values below 10% highlighted in bold.

Table 6: Relative size of spinouts and parent and industry characteristics (panel specification)

	(1)	(2)	(3)	(4)
D_{SO}	**–2.067**	**–0.180**	**–2.140**	**–0.164**
	(0.019)	(0.011)	(0.016)	(0.011)
D_{SO} x Parent size	**–0.056**	**–0.024**	**–0.053**	**–0.024**
	(0.001)	(0.001)	(0.001)	(0.001)
D_{SO} x Parent number of industries	**0.013**	**0.044**	0.007	**0.044**
	(0.005)	(0.003)	(0.005)	(0.003)
D_{SO} x Industry capital intensity	**0.120**	**0.034**	**0.130**	**0.036**
	(0.002)	(0.002)	(0.002)	(0.001)
D_{SO} x Industry human capital intensity	**0.019**	**0.010**		
	(0.005)	(0.003)		
D_{SO} x Industry analyst forecast error			**0.048**	**0.031**
			(0.012)	(0.007)
Parent size	**0.131**	**0.051**	**0.128**	**0.051**
	(0.001)	(0.001)	(0.001)	(0.001)
Parent number of industries	**–0.172**	**–0.090**	**–0.165**	**–0.090**
	(0.002)	(0.001)	(0.002)	(0.001)
Controls				
D_{SO} x Industry R&D intensity	**–2.804**	**–0.473**	**–2.745**	**–0.425**
	(0.174)	(0.108)	(0.174)	(0.108)
D_{SO} x Industry advertising intensity	**2.641**	**0.416**	**2.590**	**0.347**
	(0.134)	(0.085)	(0.133)	(0.083)
D_{SO} x Industry growth	**0.017**	**0.011**	**0.019**	**–0.011**
	(0.004)	(0.003)	(0.004)	(0.003)
D_{SO} x Parent wage	**0.057**	**0.037**	**0.079**	**–0.034**
	(0.004)	(0.002)	(0.003)	(0.002)
D_{SO} x Parent age	**0.196**	0.003	**0.210**	–0.002
	(0.003)	(0.002)	(0.003)	(0.002)
D_{SO} x Initial size of new venture		**0.025**		**–0.025**
		(0.002)		(0.002)
D_{SO} x New venture age		**0.062**		**0.061**
		(0.002)		(0.002)
Parent wage	**0.073**	**0.060**	**–0.097**	**0.059**
	(0.003)	(0.002)	(0.003)	(0.002)
Parent age	0.212	0.012	**–0.226**	**–0.013**
	(0.003)	(0.002)	(0.003)	(0.002)
Initial size of new venture		**0.751**		**0.752**
		(0.001)		(0.001)
New venture age		**0.160**		**0.160**
		(0.001)		(0.001)
N	9,340,000	9,340,000	9,340,000	9,340,000
R^2	0.330	0.716	0.329	0.716
Fixed effects	St–ind.–year	St–ind.–year	St–ind.–year	St–ind.–year

Robust standard errors clustered by new venture in parentheses. Results with state-industry-year-initial size fixed effects provided in Online Appendix Table A6b. Coefficients with *p*-values below 10% highlighted in bold.

Table 7: Relative survival of spinouts and parent and industry characteristics (age-specific OLS estimates)

Panel A	**Age 3**	**Age 5**	**Age 7**	**Age 3**	**Age 5**	**Age 7**
D_{SO}	**-0.534**	**-0.560**	**-0.506**	**-0.376**	**-0.371**	**-0.311**
	(0.047)	(0.045)	(0.045)	(0.081)	(0.075)	(0.070)
D_{SO} x Parent size	0.0002	-0.006	-0.007	0.002	-0.003	-0.004
	(0.006)	(0.006)	(0.005)	(0.008)	(0.008)	(0.007)
D_{SO} x Parent number of industries	**0.030**	**0.040**	**0.041**	**0.033**	**0.044**	**0.044**
	(0.013)	(0.012)	(0.010)	(0.017)	(0.015)	(0.014)
D_{SO} x Industry capital intensity	0.006	0.003	-0.0001	-0.001	-0.004	-0.008
	(0.005)	(0.007)	(0.006)	(0.007)	(0.008)	(0.008)
D_{SO} x Industry human capital intensity	**0.063**	**0.091**	**0.090**	**0.046**	**0.071**	**0.072**
	(0.013)	(0.016)	(0.015)	(0.018)	(0.021)	(0.019)
Parent size	**-0.011**	-0.004	-0.001	**-0.017**	-0.010	-0.006
	(0.006)	(0.006)	(0.005)	(0.008)	(0.008)	(0.007)
Parent number of industries	**-0.025**	**-0.037**	**-0.038**	-0.016	**-0.031**	**-0.033**
	(0.013)	(0.011)	(0.010)	(0.016)	(0.014)	(0.013)
N	1,628,000	1,628,000	1,628,000	1,628,000	1,628,000	1,628,000
R^2	0.351	0.381	0.390	0.562	0.599	0.615

Panel B	**Age 3**	**Age 5**	**Age 7**	**Age 3**	**Age 5**	**Age 7**
D_{SO}	**-0.425**	**-0.242**	**-0.403**	**-0.292**	**-0.425**	**-0.242**
	(0.049)	(0.068)	(0.046)	(0.077)	(0.049)	(0.068)
D_{SO} x Parent size	0.000	-0.003	-0.006	0.002	0.000	-0.003
	(0.007)	(0.008)	(0.007)	(0.008)	(0.007)	(0.008)
D_{SO} x Parent number of industries	**0.029**	**0.042**	**0.039**	**0.032**	**0.029**	**0.042**
	(0.013)	(0.015)	(0.012)	(0.017)	(0.013)	(0.015)
D_{SO} x Industry capital intensity	0.019	0.010	**0.022**	0.008	**0.019**	0.010
	(0.006)	(0.009)	(0.008)	(0.008)	(0.006)	(0.009)
D_{SO} x Ind. analyst forecast error	**0.023**	**0.017**	**0.015**	**0.024**	**0.023**	**0.017**
	(0.005)	(0.007)	(0.008)	(0.008)	(0.005)	(0.007)
Parent size	**-0.012**	-0.010	-0.005	**-0.017**	**-0.012**	-0.010
	(0.007)	(0.008)	(0.007)	(0.008)	(0.007)	(0.008)
Parent number of industries	**-0.024**	**-0.028**	**-0.035**	-0.015	**-0.024**	**-0.028**
	(0.013)	(0.014)	(0.012)	(0.016)	(0.013)	(0.014)
R^2	0.351	0.381	0.390	0.562	0.599	0.615
N	1,628,000	1,628,000	1,628,000	1,628,000	1,628,000	1,628,000

Coefficients on controls not presented. Robust std. errors clustered by NAICS 4 industry in parentheses. State-industry-year fixed effects included in the first four columns; initial size-state-industry-year fixed effects included in the last three columns. *p*-values below 10% highlighted in bold.

Table 8: Relative hazard of exit for spinouts (margins from survival models)

	(1) Cox	(2) Cox	(3) Cox	(4) Cox	(5) Weibull	(6) Weibull
Parent size	**0.049**	**0.052**	**0.035**	**0.058**	**0.053**	**0.058**
	(0.007)	(0.006)	(0.004)	(0.006)	(0.009)	(0.008)
Parent number of industries	**–0.732**	**–0.606**	**–0.391**	**–0.544**	**–0.891**	**–0.733**
	(0.029)	(0.024)	(0.021)	(0.027)	(0.036)	(0.030)
Industry capital intensity	**0.048**	**–0.181**	–0.004	**–0.216**	**0.049**	**–0.229**
	(0.011)	(0.009)	(0.007)	(0.011)	(0.013)	(0.011)
Industry human capital intensity	**–1.531**		**–0.817**		**–1.883**	
	(0.043)		(0.034)		(0.054)	
Industry analyst forecast error		**–0.552**		**–0.242**		**–0.665**
		(0.054)		(0.054)		(0.066)
Controls						
Industry R&D intensity	**–1.727**	**–6.582**	**0.064**	**–10.690**	**–2.165**	**–8.015**
	(0.624)	(0.537)	(0.016)	(0.674)	(0.776)	(0.665)
Industry advertising intensity	**8.977**	**17.170**	**8.865**	**19.860**	**11.030**	**20.950**
	(0.676)	(0.631)	(0.543)	(0.889)	(0.840)	(0.785)
Industry growth	**–0.135**	**–0.066**	–0.020	0.021	**–0.171**	**–0.084**
	(0.035)	(0.029)	(0.021)	(0.029)	(0.043)	(0.035)
Parent wage	**–1.135**	**–1.339**	**–0.476**	**–0.885**	**–1.394**	**–1.630**
	(0.034)	(0.037)	(0.023)	(0.037)	(0.044)	(0.047)
Parent age	**0.136**	**0.066**	**0.050**	**0.034**	**0.165**	**0.078**
	(0.018)	(0.015)	(0.010)	(0.014)	(0.022)	(0.018)
N	1,628,000	1,628,000	1,628,000	1,628,000	1,628,000	1,628,000
Fixed effects	State, year	State, year	State, Naics4, year	State, Naics4, year	State, year	State, year

Based on the underlying Cox and Weibull models, we compute dy/dx for each of the above variables for SO and INC separately and then take the difference between the two. This difference and its standard error are presented. Robust standard errors clustered by new venture in parentheses. Underlying coefficients from the Cox and Weibull models presented in Online Appendix Table A8a. Coefficients with *p*-values below 10% highlighted in bold.